STATISTICAL HORIZONS

# Latent Class Analysis

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# LATENT CLASS ANALYSIS

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Statistical Horizons

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## INSTRUCTOR

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## OVERVIEW OF WORKSHOP (DAY 1)

- Introduction to latent class analysis (LCA)
- The LCA mathematical model
- Latent class homogeneity and separation
- Brief SAS tutorial
- SAS PROC LCA demo

- Model identification, selection, starting values
- Multiple-groups LCA
- Measurement invariance across groups

## OVERVIEW OF WORKSHOP (DAY 2)

- Brief review of binary and multinomial logistic regression
- LCA with covariates
- LCA with a distal outcome
- LCA for repeated measures

- Introduction to latent transition analysis (LTA)
- The LTA mathematical model
- SAS PROC LTA demo
- LCA and LTA in professional writing and grant proposals
- Open discussion

## Abbreviations

- Throughout course, remember that:
- **LCA** stands for latent class analysis
- **LTA** stands for latent transition analysis (a longitudinal extension of LCA)

## Introduction to LCA, Model specification

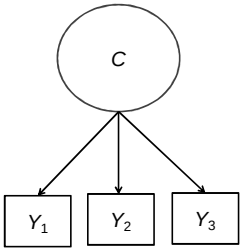
## Introduction to LCA: Some basic Ideas

- Individuals can be divided into subgroups, or latent classes, based on unobserved construct
- True class membership is unknown
- Latent classes are mutually exclusive and exhaustive

## Ideas underlying LCA

- Measurement of that construct typically based on several categorical indicators
- There is error associated with the measurement of the latent classes
- Like confirmatory factor analysis (specify number of classes), but latent variable is categorical

## Graphical depiction of latent class variable




- *C* is the latent class variable
- $Y_1$, $Y_2$, $Y_3$ are three observed indicators of *C*

## Parameters estimated in LCA

- Latent class membership probabilities
  - *e.g. probability of membership in HIGH DEPRESSION latent class*
- Item-response probabilities
  - *e.g. probability of reporting Felt Lonely given membership in HIGH DEPRESSION latent class*

## Brief example of LCA: Depression in adolescence

- From Lanza, Flaherty, & Collins (2003)
- Eight indicators of adolescent depression ($2^8$=256 possible response patterns):

**Sad**
- Couldn't shake blues
- Felt depressed
- Felt lonely
- Felt sad

**Disliked**
- People unfriendly
- Disliked by people

**Failure**
- Life was failure
- Life not worth living

## Brief example of LCA: Depression in adolescence

Five latent classes of depression:

| Latent Class | Prevalence |
|---|---|
| No depression | 41% |
| Sad | 18% |
| Disliked | 17% |
| Sad and disliked | 15% |
| High depression | 9% |

## Example of LCA: Drinking classes in 12th grade

- Data from 2004 cohort of Monitoring the Future public release
- *N*=2490 high school seniors who answered at least one question on alcohol use (48% boys, 52% girls)
- Goals of study: to explore alcohol use behavior among high school seniors; to explore gender differences in measurement and in behavior

## Example of LCA: Drinking classes in 12th grade

Seven indicators of drinking behavior:

| Item | Proportion 'Yes' |
|---|---|
| Lifetime alcohol use | 82% |
| Past-year alcohol use | 73% |
| Past-month alcohol use | 50% |
| Lifetime drunkenness | 57% |
| Past-year drunkenness | 49% |
| Past-month drunkenness | 29% |
| 5+ drinks in past 2 weeks | 26% |

## We will use LCA to:

- Identify and describe underlying classes of drinking behavior in 12th grade students
- Include grouping variable (gender)
  - Examine gender differences in behavior
  - Test for measurement invariance across males and females

## Selecting the number of classes

| Classes | $G^2$ | df | AIC | BIC | BLRT |
|---|---|---|---|---|---|
| 1 | 9510 | 120 | 9524 | 9564 | NA |
| 2 | 3019 | 112 | 3049 | 3137 | .01 |
| 3 | 911 | 104 | 957 | 1091 | .01 |
| 4 | 209 | 96 | 271 | 452 | .01 |
| 5 | 4 | 88 | 81 | 308 | .01 |
| 6 | 4 | 80 | 98 | 372 | .08 |
| 7 | 3 | 72 | 113 | 434 | --- |

*(We will revisit this…)*

## The five-class model: $\rho, \gamma$

| | Probability of 'Yes' response | | | | |
|---|---|---|---|---|---|
| Item | Class 1 (18%) | Class 2 (22%) | Class 3 (9%) | Class 4 (17%) | Class 5 (34%) |
| Lifetime alcohol use | .00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Past-year alcohol | .00 | .61 | 1.00 | 1.00 | 1.00 |
| Past-month alcohol | .00 | .00 | 1.00 | .39 | 1.00 |
| Lifetime drunk | .00 | .24 | .29 | 1.00 | 1.00 |
| Past-year drunk | .00 | .00 | .00 | 1.00 | 1.00 |
| Past-month drunk | .00 | .00 | .00 | .00 | .92 |
| 5+ drinks past 2 wk | .00 | .00 | .16 | .00 | .73 |

***What would you name these five classes?***

## Labeling the classes

| | High probability of 'Yes' response | | | | |
|---|---|---|---|---|---|
| Item | Non-Drinkers (18%) | Experi-menters (22%) | Drinkers (9%) | Bingers (17%) | Heavy Drinkers (34%) |
| Lifetime alcohol use | | √ | √ | √ | √ |
| Past-year alcohol | | √ | √ | √ | √ |
| Past-month alcohol | | | √ | | √ |
| Lifetime drunk | | | | √ | √ |
| Past-year drunk | | | | √ | √ |
| Past-month drunk | | | | | √ |
| 5+ drinks past 2 wk | | | | | √ |

## Latent class notation

- Let *C* represent the number of latent classes, which in our example will be five, e.g. NONDRINKERS, BINGERS
  - $c = 1, \ldots C$
- 7 dichotomous items measuring the latent classes (yes/no)

## Latent class notation

- Let *Y* refer to the vector of response patterns
- Let *y* represent a particular response pattern
- Example: $y$ = (Y, Y, N, N, N, N, N)

## The traditional latent class model parameters

$\gamma_c$ = probability of membership in latent class *c* (**class membership probabilities**)

$\rho_{i|c}$ = probability of response *i* to Item 1 conditional on membership in latent class *c* (**item-response probabilities**)

## The traditional latent class model

$$P(Y = y) = \sum_{c=1}^{C} \gamma_c \prod \rho$$

– Assumption of local independence: Items are independent within each class

$$P(Y = y) = \sum_{c=1}^{C} \gamma_c \prod \rho$$

$\gamma_c$ = probability of membership in Latent Class *c*
(*e.g. probability of membership in BINGERS latent class*)

$\rho_{i|c}$ = probability of response *i* to Item 1, conditional on membership in Latent Class *c*, etc.
(*e.g. probability of reporting 'Yes' to Item 1, conditional on membership in the BINGERS latent class*)

## More about $\rho$ parameters

- The $\rho$ parameters express the relation between:
  - the discrete latent variable in a latent class analysis and
  - the observed variable indicators
- Similar conceptually to factor loadings
  - basis for interpretation of latent classes
- $\rho$'s are probabilities (between 0 and 1)

## A note on missing data

- Most LCA and LTA software can handle missing data
- Missing data mechanisms
  - **MAR (missing at random)**
    - *Missingness is completely random, or related to observed items*
  - **MNAR (missing not at random)**
    - *Missingness related to unobserved items; more difficult to adjust for this type of missingness*
- Software assumes data are MAR

## Homogeneity and Latent Class Separation

## Rho parameter interpretation

- Rho parameters analogous to factor loadings; both
  - Express relation between manifest and latent variables
  - Form basis for interpreting latent structure
- But
  - Factor loadings are *b*-weights
  - Rho parameters are PROBABILITIES

## How would you interpret these latent classes?

| Probability of correctly performing practical task | Latent Class 1 | Latent Class 2 |
|---|---|---|
| Task 1 | Low | High |
| Task 2 | Low | High |
| Task 3 | Low | High |
| Task 4 | Low | High |
| Task 5 | Low | High |

## How would you interpret these latent classes?

| Probability of Responding 'Yes' | Latent Class 1 | Latent Class 2 |
|---|---|---|
| Tried Alcohol | Low | High |
| Been Drunk | Low | High |
| Tried Tobacco | Low | High |
| Tried Marijuana | Low | High |
| Tried Meth | Low | High |

## How would you interpret these latent classes?

| Probability of Responding 'Yes' | Latent Class 1 | Latent Class 2 | Latent Class 3 |
|---|---|---|---|
| Tried Alcohol | Low | High | High |
| Been Drunk | Low | High | High |
| Tried Tobacco | Low | High | High |
| Tried Marijuana | Low | Low | High |
| Tried Meth | Low | Low | High |

## How would you interpret these latent classes?

| Probability of Responding 'Yes' | Latent Class 1 | Latent Class 2 | Latent Class 3 | Latent Class 4 |
|---|---|---|---|---|
| Tried Alcohol | Low | High | High | High |
| Been Drunk | Low | Low | High | High |
| Tried Tobacco | Low | High | High | High |
| Tried Marijuana | Low | Low | Low | High |
| Tried Meth | Low | Low | Low | High |

## Rho parameter interpretation

- $0 \leq \text{rho} \leq 1$
- When latent variable completely predicts manifest variable, rho = 0 OR rho =1
- When latent variable does not completely predict manifest variable, $0 < \text{rho} < 1$
- When latent variable does not at all predict manifest variable,
  rho = marginal probability for item
- So if we are trying to measure a latent variable, what kind of rho's do we like?

## Characteristics of patterns of rho parameters

- **Homogeneity**: degree to which rho parameters for a particular latent class are close to 0 and 1
- Individuals in a class are similar to each other

## Characteristics of patterns of rho parameters

- High homogeneity

| Probability of correctly performing practical task | Latent Class 1 | Latent Class 2 |
|---|---|---|
| Task 1 | .10 | .85 |
| Task 2 | .15 | .90 |
| Task 3 | .05 | .89 |
| Task 4 | .10 | .95 |
| Task 5 | .12 | .90 |

## Characteristics of patterns of rho parameters

- Low homogeneity

| Probability of correctly performing practical task | Latent Class 1 | Latent Class 2 |
|---|---|---|
| Task 1 | .45 | .50 |
| Task 2 | .48 | .55 |
| Task 3 | .50 | .51 |
| Task 4 | .49 | .56 |
| Task 5 | .46 | .58 |

## Characteristics of patterns of rho parameters

- High homogeneity

| Probability of Responding 'Yes' | Latent Class 1 | Latent Class 2 | Latent Class 3 | Latent Class 4 |
|---|---|---|---|---|
| Tried Alcohol | .95 | .90 | .95 | .99 |
| Been Drunk | .99 | .10 | .92 | .97 |
| Tried Tobacco | .96 | .93 | .94 | .89 |
| Tried Marijuana | .89 | .05 | .10 | .88 |
| Tried Meth | .91 | .10 | .07 | .93 |

## Characteristics of patterns of rho parameters

- Low homogeneity

| Probability of Responding 'Yes' | Latent Class 1 | Latent Class 2 | Latent Class 3 | Latent Class 4 |
|---|---|---|---|---|
| Tried Alcohol | .45 | .55 | .52 | .55 |
| Been Drunk | .48 | .45 | .56 | .50 |
| Tried Tobacco | .40 | .56 | .50 | .54 |
| Tried Marijuana | .45 | .48 | .43 | .56 |
| Tried Meth | .47 | .43 | .46 | .52 |

## Characteristics of patterns of rho parameters

- **Latent class separation**: degree to which latent classes can clearly be distinguished from each other

## Characteristics of patterns of rho parameters

- High homogeneity and high latent class separation

| Probability of correctly performing practical task | Latent Class 1 | Latent Class 2 |
|---|---|---|
| Task 1 | .10 | .91 |
| Task 2 | .15 | .90 |
| Task 3 | .05 | .89 |
| Task 4 | .10 | .95 |
| Task 5 | .12 | .90 |

## Characteristics of patterns of rho parameters

- High homogeneity and low latent class separation

| Probability of correctly performing practical task | Latent Class 1 | Latent Class 2 |
|---|---|---|
| Task 1 | .80 | .91 |
| Task 2 | .82 | .90 |
| Task 3 | .81 | .89 |
| Task 4 | .80 | .95 |
| Task 5 | .84 | .90 |

## Characteristics of patterns of rho parameters

- Homogeneity analogous to concept of saturation in factor analysis
- Latent class separation analogous to concept of simple structure in factor analysis
- You can have
  - High homogeneity, high latent class separation
  - High homogeneity, low latent class separation
  - Low homogeneity, low latent class separation
  - But not low homogeneity, high latent class separation

## So what kind of pattern do we want?

- Depends on your perspective
  - You might be using LCA with a "discovery" perspective
  - OR you might be using LCA with a "measurement" perspective
- Neither is better, but they are subtly different

## "Measurement" perspective

- Purpose: to establish the latent variable and a good way to measure it
- May take steps to improve homogeneity and latent class separation, e.g.
  - May discard some variables that contribute to heterogeneity
  - May impose parameter restrictions to simplify model
  - May choose number of latent classes partly on this basis

## "Discovery" perspective

- Purpose: to make sense out of a large contingency table
- Interpretation something like: "people in Latent Class 1 had a 40 percent probability of correctly performing Task 1"
- Homogeneity and latent class separation somewhat less important from this perspective

## SAS tutorial, PROC LCA demo, Exercise1